

# Impact of Automotive Camera Production Tolerances on Computer Vision



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## 1 INTRODUCTION:

We use cameras to capture images on roads to add visual awareness to automotive driving. This is essential for Computer Vision (CV) tasks like Object Detection.

Fisheye cameras are useful giving a wide field-of-view to capture 360° surround-view of an automotive vehicle.

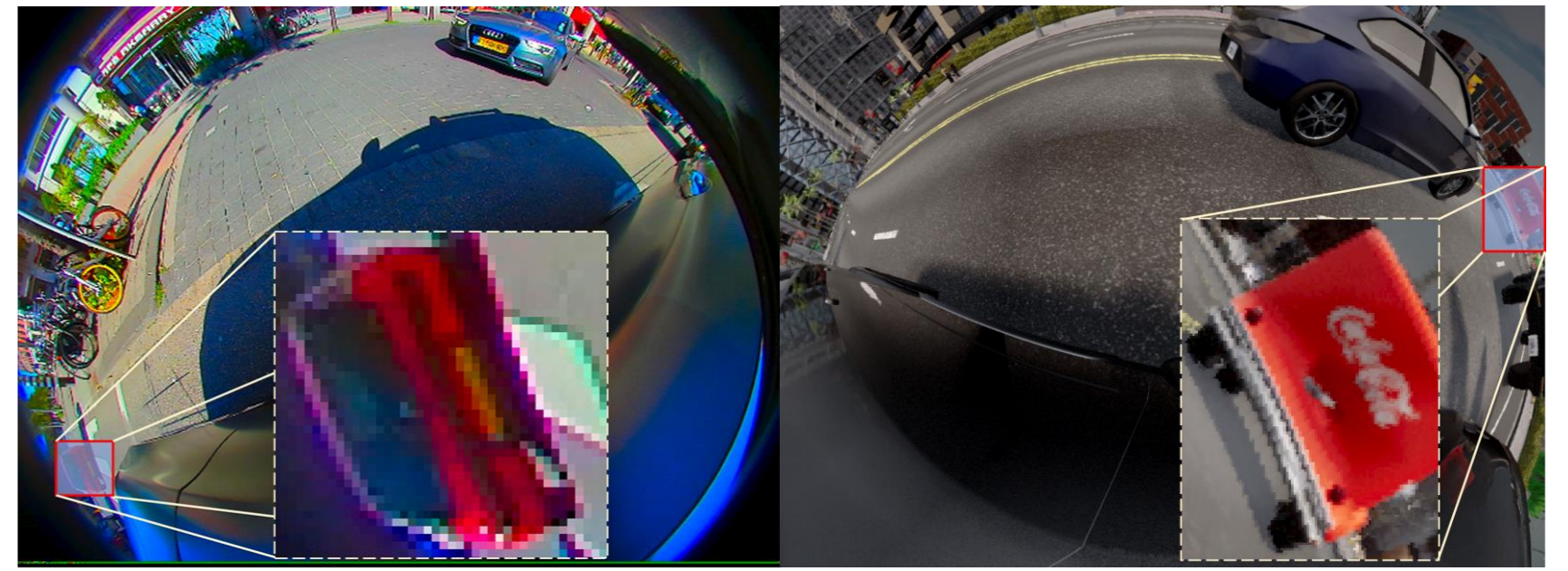
Cameras should be designed knowing how Computer Vision behaves with a lens.

Establishing a **relationship** between the **fisheye camera design** and **Computer Vision (CV)** is the main objective of this research.

Potential Contributions:

- Investigate Image Degradation and Optical Artifacts of cameras
- Understand how Computer Vision behaves given changes in Optical Artifacts
- Could this research contribute to reducing the discarding of cameras in the production line?

## 2 AUTOMOTIVE SIMULATION:



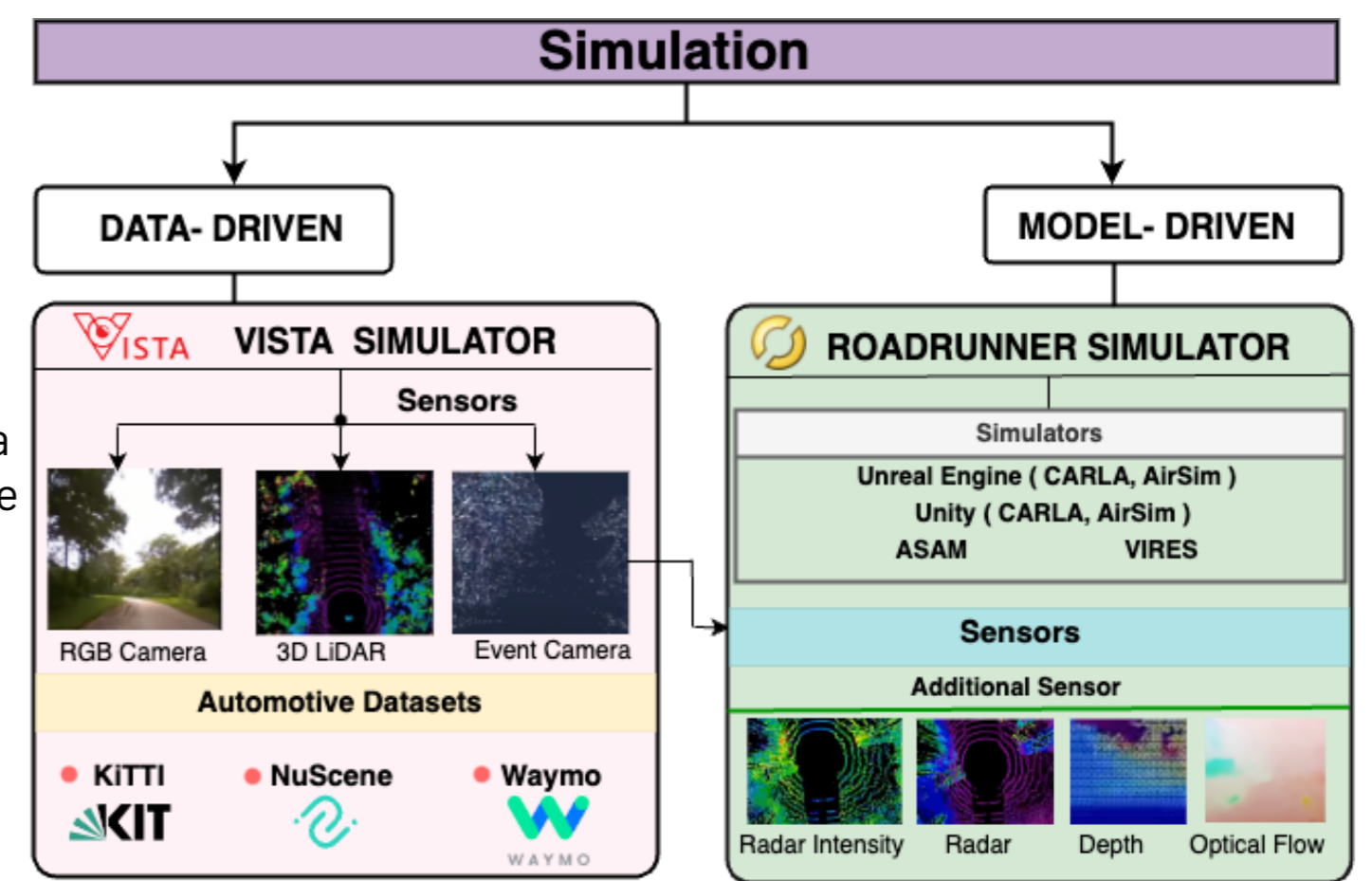
The above shows the **real-life (left)** versus the **simulation (right)** of fisheye images. Notice the distinct image quality gap between both, where the outline of the red car in real-life has a clear colour degradation at the outlines called, **Chromatic Aberration**, a common Optical Artifact found in cameras. Optical Artifacts such as this should be accounted for in automotive simulators.

**Two categories of simulation:**

• **Model-Driven** → created using computer programs

• **Data-Driven** → Publicly gathered data synthesized for a more photorealistic appearance

**Simulation needs to integrate with cameras for more realistic simulation**

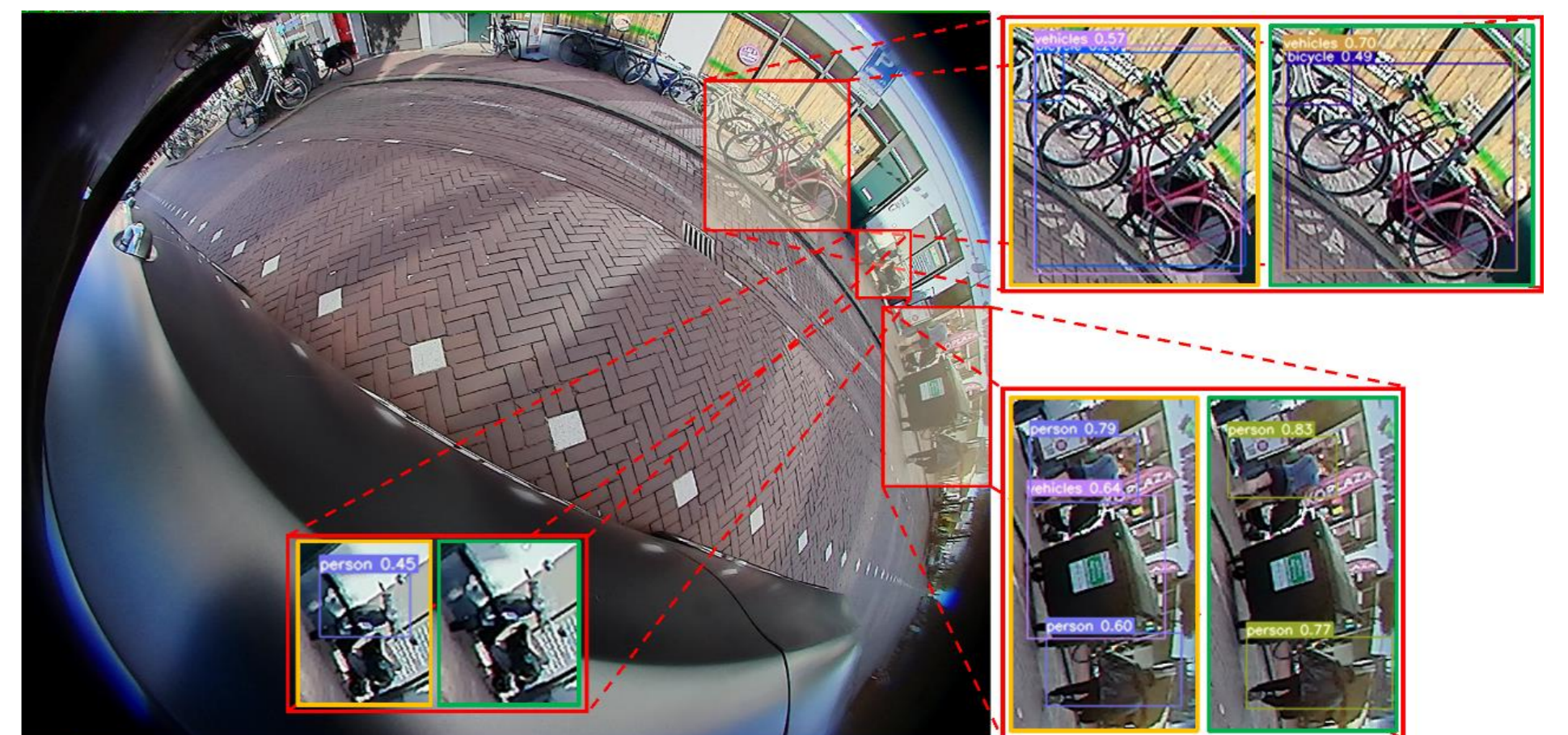


## 3 AUTOMOTIVE CAMERAS:



Automotive Cameras vary depending on the Field of View and the nature of the camera design susceptible to driving conditions. Notable Optical Artifacts that degrade image quality are **Chromatic Aberration, Astigmatism, Vignetting and Geometric Distortion**.

## 4 AUTOMOTIVE COMPUTER VISION:



YOLOv7 inference **regions of interest (ROIs) (red box)** on the **Woodscape** left camera image was performed above. Qualitative results show both **training from scratch (orange box)** and **transfer learning (green box)**. Notice the misclassification of object types in both instances. The orientation of the object in the image due to its location can confound an object detection network. Note: the pre-trained model used in **transfer learning was pre-trained on the MS COCO dataset**.

Statistical results lack information on optical quality performance. A new metric system needs to be devised to accommodate both **Optical and Computer Vision Performance**.

*Acknowledgements:*

This work was supported, in part, by the Science Foundation Ireland grant 13/RC/2094 P2 and co-funded under the European Regional Development Fund through the Southern & Eastern Regional Operational Programme to Lero.

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